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MODELING THE IMPACT OF NATURAL AND SECURITY HAZARDS IN AN LNG PROCESSING FACILITITY

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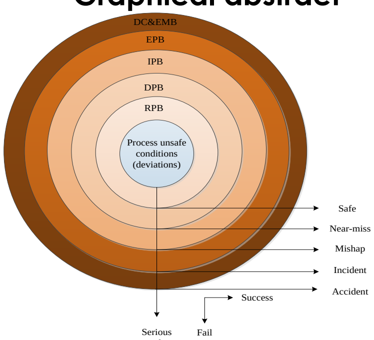
Graphical abstract



Abstract

Development of accident models based on cause and effect relationships facilitates the formulation of accident prevention and mitigation plans in the Chemical Process Industries (CPIs). In this paper, failures of accident prevention barriers triggered by man-made and natural hazards are causally modeled using Fault Trees (FTs) models. Additionally, updated technique of FTs basic and top events failure probabilities was applied using Hierarchy Bayesian Approach (HBA) based on basic events precursor data. This updated methodology overcomes the uncertainty limitation in the determination of FTs reliability data, as well as converge them into their accurate values. Moreover, it provides valuable information supporting risk based decision. The methodology was applied to LNG pipeline and liquefaction plant Dispersion Prevention Barrier (DPB). The result shows the capability of the methodology to model natural and security hazards (NE&ISHs) in both qualitative and quantitative manners, as well as, to update FT events failure probabilities through the use of the precursor data to the HBA. Outcomes demonstrate that the average posterior failure probability of DPB of that particular case study increased from 0.0613 to 0.204232 which represents a 3.33 times increment compared with the prior.

Keywords: Accident Modeling, Intentional Security Hazards, Natural Hazards, Hierarchy Bayesian Approach (HBA), Precursor data.

Abstrak

Pembangunan model kemalangan berdasarkan sebab dan akibat antara kemudahan hubungan penggubalan pencegahan dan mitigasi pelan kemalangan dalam Proses Kimia Industri CPIs . Dalam kajianini , kegagalan pencegahan kemalangan dicetuskan oleh faktor buatan manusia dan bencana alam semulajadi adalah dimodelkan menggunakan Fault Trees (FTS) model. Selain itu, teknik FTS kebarangkalian kegagalan peristiwa asas dan popular telah dikemaskini dengan menggunakan Hierarki Pendekatan Bayesian (HBA) berdasarkan pelopor data peristiwa asas. Metodologi yang telah dikemaskini mengatasi masalah had ketidakpastian dalam penentuan kebolehpercayaan data FTS, dan juga menghubungkan data-data tersebut pada nilai-nilai yang tepat, tambahan pula; ia menyediakan maklumat yang berharga untuk menyokong keputusan berdasarkan risiko.Metodologi telah digunakan untuk saluran paip LNG dan loji pencairan Serakan Pencegahan Barrier (DPB). Hasilnya menunjukkan keupayaan kaedah untuk natural and security hazards (NE & ISHs) model dalam mengikut cara kedua-dua kualitatif dan kuantitatif, dan juga, untuk mengemaskini kegagalan peristiwa FT kebarangkalian melalui penggunaan data pelopor kepada HBA . Hasil menunjukkan bahawa purata kebarangkalian kegagalan posterior DPB hasil darikajian kes tertentu telah meningkat dari 0.0613 ke 0.204232 yang mewakili 3.33 kali peningkatan berbanding dengan sebelumnya.

Kata kunci: Pemodelan Kemalangan, Sengaja Bahaya Keselamatan, Bencana Alam, Pendekatan Bayesian Hierarki (HBA), Data Prekursor.

1.0 INTRODUCTION

In the chemical process industry, accidents and loss of containment are often the result of material and/or energy releases triggered by one or combinations of process hazards such as technical and operational errors, human intervention faults, as well as management and organizational factors [1]. Due to the complex nature of these factors, there is a need to systematically model their interactions and relationships with the succeeding adverse consequences. The modeling of why failures are triggered and the occurrence of the subsequent accident is called accident modeling [2]. Over the years, a number of accident models have been put forward [3], with some specifically addressing hazards associated with processes, natural events and security.

Although process hazards are the main reason for the loss of containment (LOC) in process industries, other hazards such as unwanted natural phenomena and intentional security acts threats also contributed substantially [4-8]. In fact, natural phenomena and intentional security related hazards are likely to cause more severe impacts due to wide area of coverage as well as the high possibilities of simultaneous and cascading accidents. In addition, these hazards also hamper emergency responses and rescue plans, thus making the affected people and properties more vulnerable.

Accidents triggered by natural events are known in the field of CPI as Na-Tech accidents. An earlier study on Na-Tech related accidents in the CPI in the USA revealed the varying impacts depending on the frequency and severity on the events occurring in specific regions, but it was nevertheless alarming since the trend of Na-Tech accidents was on the rise [9]. The various risks based on climate change and geographical aspects are also thought to be the dominant factors that influence the increase in numerous incidents [10, 11]. To name a few, some examples of Na-Tech related accidents can be found in [4, 12-16]. In addition to losses of human life and property, Na-Tech disasters also cause considerable ecological damages to soil and groundwater due to leakage of chemicals, polluted drinking water and endangerment to the health of humans and animals [17].

Similarly to Na-Tech, security hazards also contribute to accidents in the CPI in many possible ways leading to release of toxic and/or flammable materials and their subsequent unwanted events [7, 8]. The call for considering these hazards came from the available statistical information of accidents that have been taken place in CPIs. For example, 88 security related accidents to oil and gas facilities worldwide were reported in the period of 1980-2000 [18]. In another report, *Chang and Lin* [19] listed 18 CPI storage tank accidents triggered by terrorism and sabotage in the period of 1960-2003, and showed that security hazards were the fourth frequent causes of storage tanks accidents.

A number of methodologies have been developed to assess the CPI risks due to natural events, as well as to prevent and mitigate their consequences. Among these, quantitative risk assessment (QRA) methodology is regarded as the most powerful tool [15, 20-28]. However, a full-blown QRA requires huge resources in terms of time, data, and expertise. To overcome this issue, *Busini et. al.,* [29] developed a qualitative short cut method to assess risk due to seismic event, and the methodology has three hierarchies of Na-Tech that lead to produce three key hazard indicators (KHI) for fires, toxic dispersion, and explosion. This short cut methodology showed a good agreement comparing with QRA [29]. *Cruz and Okada* [14] developed a rapid Na-Tech risk assessment (RNRA) methodology that identifies, quantifies, and analyzes the risk posed by the presence of hazardous materials in areas subject to natural hazard risk. However, these methodologies focus only on specific natural events, whereas in actual situations, different natural events may combine to produce new accident modes. Most of these methodologies focus only on a specific natural event, whereas different natural events may combine and produce some new accident modes. Typical of simplified methods, some aspects that may be important are neglected e.g. RNRA methodology slightly considers the direct impacts on the environment, as well as it doesn't include other important impacts such as economic, psychological, and potential processing hazmat releases impacts from vessels and pipeline.

Similarly, assessment methodologies for security risks have also been developed. *Jaeger* [30] proposed a systematic CPI security vulnerability assessment methodology for terrorist or criminal attacks. This was followed by a series of development by Gupta and co-workers [5, 31]. Initially, a three stage methodology was proposed to assess the individual and overall risk of the facility. The stages were Threat Analysis (TA), Vulnerability Analysis (VA), and Security Risk Factor Table (SRFT) [5, 31]. In a later work, the SRFT was extended by adding a Stepped Matrix Procedure (SMP) to study the vulnerability among the domino effect scenario through the use of threat events [32]. Along another route, Reniers and co-workers [33-35] developed methodologies based on game theory to evaluate different strategic precautionary measures to deal with security threats. Later *Reniers et al.,* [36] proposed a Threat Assessment Review Planning (TARP) methodology that optimizes threat assessment planning activities through systematic planning procedure that objectively determines the need for threat assessments, in each facility and can be extended to organization-wide scale.

This paper introduces a methodology to assess risk to CPI process facility caused by natural events (including earthquake, flooding, lightening, and storm) and intentional security acts in one framework. The proposed methodology has quantitative outcomes and dynamics features through the use of real time data and hierarchal Bayesian approach. This updating mechanism of prior knowledge supports risk based decision through prioritizing facilities plans and management of change for safer plants against these hazards.

2.0 METHODOLOGY FRAMEWORK

2.1 Modeling CPI Natural and Intentional Security Hazards (NE&ISHs)

Prevention barriers (PBs) of chemical processes can be introduced sequentially as release (RPB), dispresion (DPB), ignition (IPB), escalation (EPB), and damage control & emergency management (DC&EMPB) [1, 37]. Note that the basic layer of protection, i.e., process control, alarm, interlock and relief devices, is considered as part of RPB that prevents process upset from being propagated to release. Abnormal release of unwanted initiating event can occur if all four layer of protections failed, either consecutively or simultaneously or due to maintenance and structural failures. Fig 1 shows accident sequence in CPI with the end-state events depending on the success or failure of the prevention barriers.

Using this modeling paradigm, the causal models of failures triggered by natural hazards and deliberate acts to all accident prevention barriers of a LNG processing facility, i.e., RPB, DPB, IPB, EPB, DC&EMPB, are developed using Fault Tree models. Within each FT model, all potential hazards associated to plant operation and management aspects, including operational and technical, structure and design, components, human, and, management and organizational factors, are considered and incorporated. Models' outcomes provide quantitative estimations of the contributions of Na-Tech and Intentional Security Hazards (NE&ISHs) on the failure probabilities of process prevention barriers.

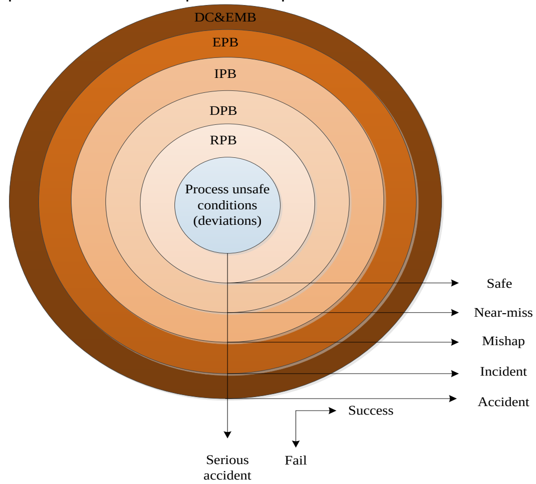


Figure 1 Prevention barriers applied in CPI accident sequence

Using this modeling paradigm, the causal models of failures triggered by natural hazards and deliberate acts to all accident prevention barriers of a LNG processing facility, i.e., RPB, DPB, IPB, EPB, DC&EMPB, are developed using Fault Tree models. Within each FT model, all potential hazards associated to plant operation and management aspects, including operational and technical, structure and design, components, human, and, management and organizational factors, are considered and incorporated. Models' outcomes provide quantitative estimations of the contributions of Na-Tech and Intentional Security Hazards (NE&ISHs) on the failure probabilities of process prevention barriers.

2.2 Barriers and Basic Events Probability Updating

The failure probabilities obtained from the previous part are the priors of accident prevention barriers due to NE&ISHs. These priors are estimated using the reliability data available on basic events, as well as experts' opinions for cases where data are unattainable. To improve confidence of the reliablilty data, updating methodology based plant's precursor data is introduced. The updates also provide dynamics to the prevention barriers and basic events failure probabilities, which in turn help supporting risk based decisions for more effective management plans. This can be conveniently achieved by employing Bayesian approach [38-48].

In Bayesian approach, the prior and likelihood functions are represented by conjugate pair of distribution functions e.g. Gamma-Poisson and Beta-Binomial pairs, hence Gamma and Beta are the priors, and Poisson and Binomial are the likelihood functions. Since the priors have significant effects on the estimated posteriors, a good prior knowledge is important. However, due to the lack of reliability data, the determination of prior distribution shaping parameters is not straightforward. Because of this reason, a hyper-prior distribution is used to allow a more flexible way to express the prior uncertainty and provides more consistent results [49]. In hyper-prior distribution, the shaping parameters are represented as distribution functions instead of as fixed value parameters. This model is known as hierarchy Bayesian approach HBA. HBA is multistage prior distributions that could consist of two stages or more. However, the use of more than two stages is rare in the applications [50]. The two-stage hierarchical Bayesian approach was firstly introduced by *Stan Kaplan* [51] in which the prior distribution for the parameter of interest is represented as:

$$\pi(\theta) = \int_{\Phi} \pi_1(\theta \setminus \varphi)\pi_2(\varphi)d\varphi \tag{1}$$

Here, θ is the interested parameter, φ is the vector of $(\alpha,\beta)^T$, $\pi_1(\theta\setminus\varphi)$ denotes the first stage prior, and $\pi_2(\varphi)$ denotes the hyper-prior distribution that represents the uncertainty in φ.

In this study, Poisson distribution (Eq.2) is used for each source data x in which Poisson rate (□) is the interested parameter used to determine the prior's posterior probability *π(□□\x,t)* which represents the updated failure frequency of basic event for each data source at each time interval.

$$f(x \setminus \lambda) = \frac{(\lambda t)^x e^{-\lambda t}}{x!}, \ \ for \ x \geq 0 \tag{2}$$

In order to model the variability in □ among data sources x_i, a first stage Gamma prior distribution is used. That the first stage prior in Eq. 1 will be as:

$$\pi_1(\lambda \setminus \alpha,\beta) = \frac{\beta^{\alpha} \lambda^{\alpha-1} e^{-\beta\lambda}}{\Gamma(\alpha)}, \ \ for \ x \geq 0 \tag{3}$$

Hence, α and β are the hyper parameters that are introduced as distribution functions of Gamma. Numerical optimization techniques that maximize Poisson likelihood function can be used to determine the values of the shaping hyper-prior parameters of Gamma distributions of α and β [51]. Ity is often the case that expert opinions are used to assume the hyper-prior shaping parameters as done by *Yang et. al.,* [52]. Fig. 2 represents the hierarchy Bayesian model in its Bayesian network directed acyclic graph TAG. Each TAG represents a node of a random variable of interest. The assumed parameters of α and β define the shape of the distribution and are independent of the other variables. Nevertheless, once data on the failure events are fed to the model, these values will be recomputed based on the observed data, and hence become dependent of the incident data [50].

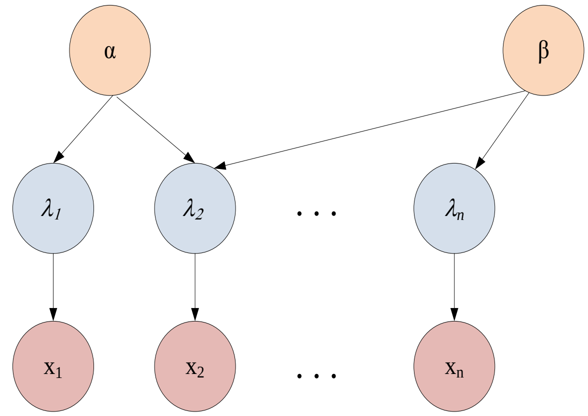


Figure 2 Directed acyclic graph for hierarchical Bayes model [50]

That, the posterior distribution of □ is obtained as the average of the posterior distributions of □□□that conditionally depends on α and β and are weighted by their posterior distributions, represented as [50]:

$$\pi(\lambda_i \setminus x,t) = \iint \pi_1(\lambda i \setminus x,t,\alpha,\beta)\pi_2(\alpha,\beta \setminus x,t)\,d\alpha\,d\beta \tag{7}$$

By using sampling technique, α and β are sampled from their joint posterior distribution, and then sampling□□ from the Gamma distribution using Markovian Chain Monte Carlo simulation MCMC (WinBUGS software) for each discrete time interval, and then the posterior failure probabilities of basic events are obtained.

3.0 CASE STUDY

The developed methodology is applied to (X) LNG liquefaction facility including pipeline (from reservoirs to liquefaction plant) and export offshore platform to estimate the failure probability of accident prevention barriers produced by NE&ISHs. Fig 3 shows the important site information of risk assessment.

3.1 Process Description

The plant productivity is 6.7 million cubic metric tons of LNG per year. The plant is fed by 1,140 million standard cubic feet of natural gas per day. It is supplied by a 320 km length pipeline with 38 inch diameter. The pipeline passes through two states in the country (Y) mainly in the desert and thinly populated region to reduce the impact to livelihoods in case of accidents. However, it also closely passes oil fields in these two states. The liquefaction plant is situated at coastal area with a distance of 25-30 km from small towns. Main highway passes approximately 2km from the plant perimeter. The liquefaction process used in the plant is propane pre-cooled mixed refrigerant (C3MR). The process units involved in operation include acid removal, dehydration, propane refrigeration, heavy hydrocarbons removal, and storage tanks. The LNG is transferred by ships through offshore platform terminal.

The plant is divided into areas as illustrated in Fig. 3. It is categorized into four different security zones of Z0, Z1, Z2 and Z3, which are low- risk areas, moderate-risk areas, high-risk areas, and critical-risk areas respectively. The pipeline is situated in low educated tribal areas that have weapons. With regards to natural events, plants from this region, from reservoirs to export platform, have not recorded high strength natural events.

3.2 Risk Assessment

LNG is a hazard substance due to its cryogenic, flammability properties, and its vapor dispersion characteristics. LNG's boiling point is (-162°C) at a pressure of 1.7 KPa. Direct contact to LNG can cause damage to both skin and metals. Its flammability in the air is within the range of 5% to 15% volume fraction. The release of natural gas or its liquefied form could produce flammable cloud, which when ignited could result to flash fire or/and vapor cloud explosion. Spillage of LNG may form a pool and forms pool fire if ignited, and if the liquid spills in water, explosion may occur due to a phenomenon known as "Rapid Phase Transition". Furthermore, the facility contains high presurrised propane in spherical tank that can produce BLEVE.

4.0 RESULT AND DISCUSSION

4.1 Barriers Prior Probability Estimation

The FT models of prevention barriers failure caused by NE&ISHs for the LNG case study are as shown in Fig4, Fig5, Fig6, Fig7, and Fig8. Basic events failure probabilities are obtained from plant's specific data, experts' opinions, and published literatures [48, 53-56]. By simulating the FTs, failure probabilities of the prevention barriers triggered by NE&SHs are obtained and shown in Table 1.

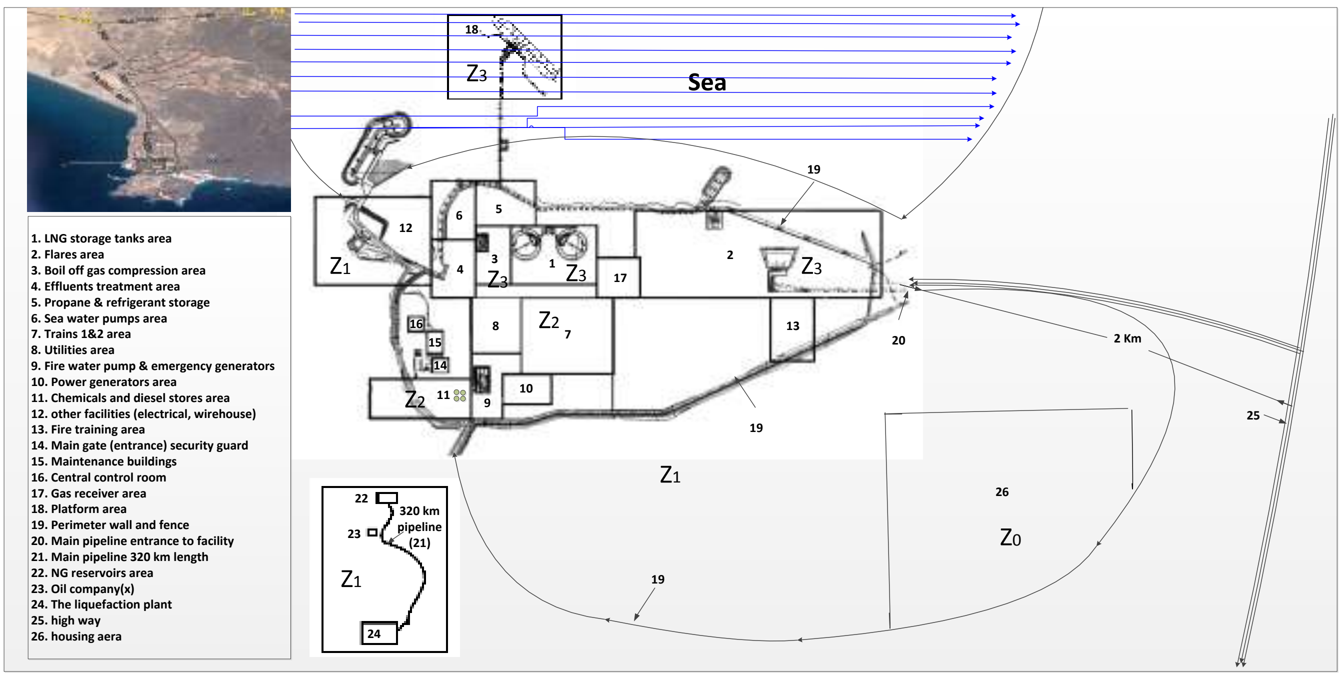


Figure 3 Important site information for risk assessment of the case study

Table 1 Barrier Failure Probabilities by NE&ISHs

No.	Top event	Prior failure probability
1	RPB	1.50E-3
2	DPB	6.13E-2
3	IPB	9.60E-2
4	EPB	2.54E-8
5	DC&EMB	2.90E-3

From Table 1, it is clear that NE&ISHs have more effects on increasing the failure probability of IPB followed by DPB, DC&EMB, RPB, and EPB respectively. The results of FTs simulation are logical due to the fact that the prevention of ignition sources triggered by NE&ISHs is a difficult target since unexpected intentional acts and high strength natural events can overcome the prior prevention plans. Ignition can be produced from equipment collapse and collision (even friction with particle carried by storm), lightning, terrorism/sabotage attacks using weapons, and disgruntled employee act with ineffective prevention. As mentioned before, NE&ISHs are usually associated with human confusion and limit human intervention accessibility leading in difficulty of controlling loss of containment LOC that increases the failure probability of the DPB, as obtained in Table 1.

4.2 Barriers and Basic Events Probability Updating

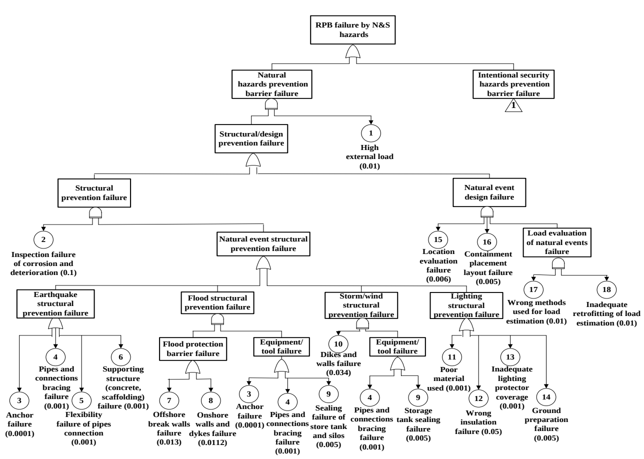
The introduced updating methodology is implemented to the DPB of the LNG case study. Precursor data of failures of basic events of DPB were collected for ten discrete time intervals (a month for each interval) as shown in Table 2.

The hyper-prior shaping parameters of α and β Gamma hyper-priors distributions are assumed as in Table 3. These assumptions are built from experts' opinions. Note that the priors means obtained from these hyper-priors parameters are equal to the one used in FT model.

The posterior failure probabilities of basic events are obtained using MCMC simulation (WinBUGS software) of the HBA with the utilization of basic events precursor data. The model was run with 10,000 burn samples, and then followed by 10,000 iterations for each chain converging into the posterior failure probabilities of basic events as declared in Table 4, and then the top event can be estimated deterministically.

The posteriors obtained show that the failure probabilities of basic events 1, 2, 4, and 7 were increased compared to their priors, whereas the positeriors of the rest of basic events were decreased. Table 5 shows the average of the posteriors of the ten intervals. These averages were compared with the priors through indication ratio that identifies the times of increase or decrease of the average to the prior, in which a ratio bigger than 1 means an increase, whereas a ratio less than 1 means a decrease. The average of DPB failure probability of the case study was increased from 0.0613 to 0.204232, which represents a 3.33 times increase compared with the prior.

This shows the importance of modified plans for basic events that have been increasing in the failure probability, and this can be done through e.g. build security towers along the 320km pipeline with suitable distance between them to cover the critical areas around pipeline that allows discovery of any abnormal acts, improve operators' skills in emergency cases caused by NE&SHs through trainings, increase patrols.



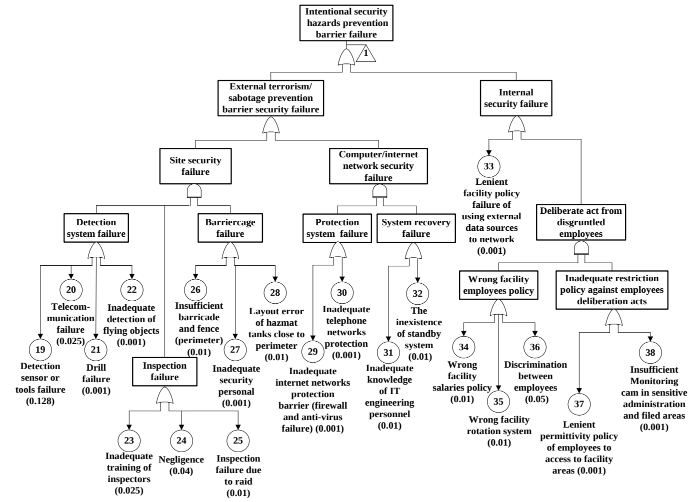


Figure 4 RPB failure caused by NE&ISHs

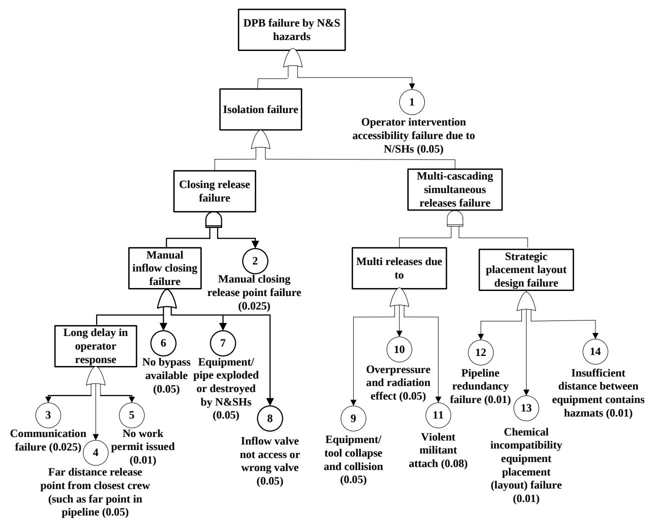


Figure 5 DPB failure caused by NE&ISHs

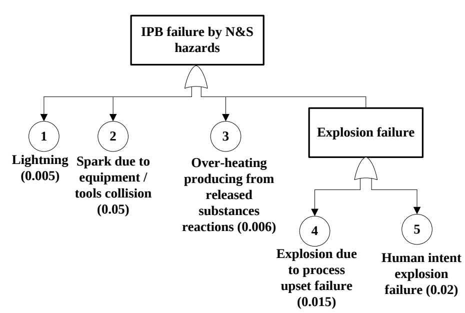


Figure 6 IPB failure caused by NE&ISHs

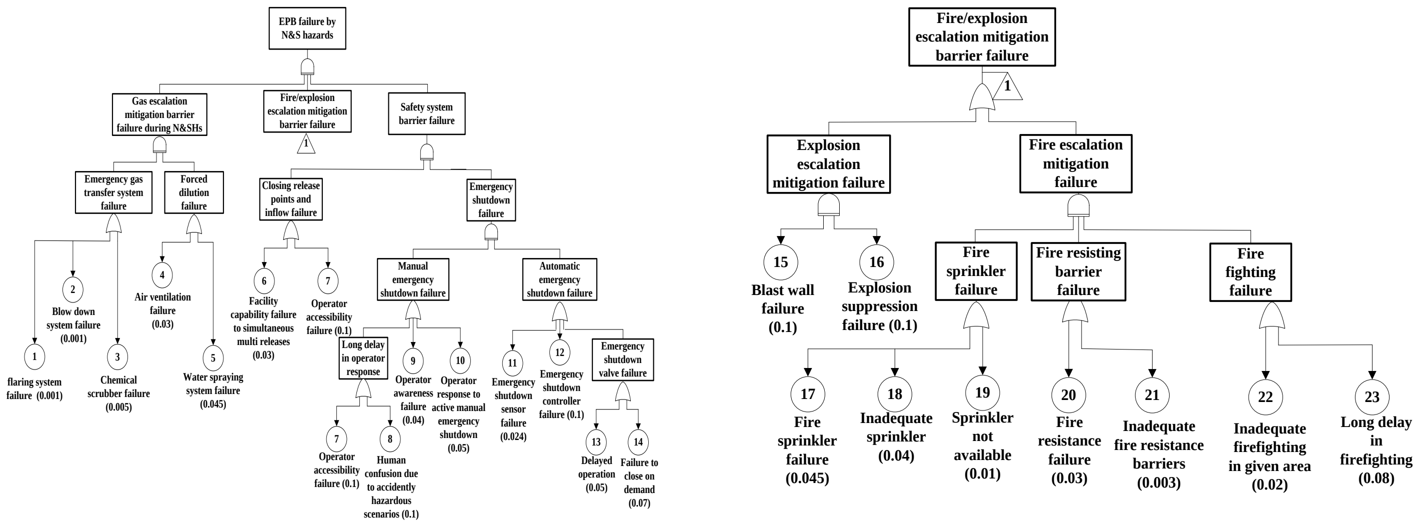


Figure 7 EPB failure caused by NE& ISHs

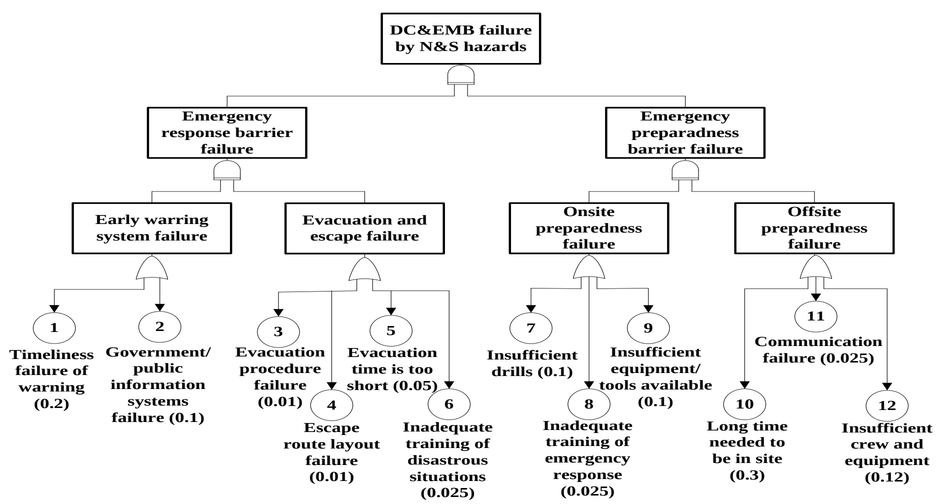


Figure 8 DC&EMB failure caused by NE&ISHs

Table 2 Plant Specific Accumulative Precursor Data of Number of Basic Events Occurrence

Interval (month)	Number of occurrence of basic events													
	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	0	1	0	0	1	0	0	0	0	0	0	0
4	2	2	0	1	0	0	2	0	0	0	0	0	0	0
5	3	2	0	1	0	0	2	0	0	0	0	0	0	0
6	4	2	0	2	0	0	3	0	0	0	0	0	0	0
7	4	2	0	2	0	0	3	0	0	0	0	0	0	0
8	5	2	0	2	0	0	3	0	0	0	0	0	0	0
9	6	2	0	3	0	0	4	0	0	0	0	0	0	0
10	7	3	0	3	0	0	5	0	0	0	1	0	0	0

Table 3 The Assumed Hyper-prior Information of Basic Events

Event	Distribution	Hyper-prior parameters		Prior mean
		□	β	
B1	Gamma	Gamma(2,0.8)	Gamma(19,0.38)	0.050
B2	Gamma	Gamma(2.1,0.7)	Gamma(33,0.275)	0.025
B3	Gamma	Gamma(3.0,1.0)	Gamma(48,0.4)	0.025
B4	Gamma	Gamma(2.0,0.8)	Gamma(14,0.28)	0.050
B5	Gamma	Gamma(1.8,0.9)	Gamma(40,0.2)	0.010
B6	Gamma	Gamma(2.1,0.6)	Gamma(21,0.3)	0.050
B7	Gamma	Gamma(2.0,0.5)	Gamma(14,0.175)	0.050
B8	Gamma	Gamma(2.1,0.7)	Gamma(21,0.35)	0.050
B9	Gamma	Gamma(3.0,1.0)	Gamma(30,0.5)	0.050
B10	Gamma	Gamma(2.1,0.6)	Gamma(21,0.3)	0.050
B11	Gamma	Gamma(3.3,0.55)	Gamma(24,0.32)	0.080
B12	Gamma	Gamma(2.5,0.625)	Gamma(26,0.325)	0.050
B13	Gamma	Gamma(2.1,0.7)	Gamma(21,0.35)	0.050
B14	Gamma	Gamma(2.1,0.6)	Gamma(21,0.3)	0.050

Table 4 Posterior Mean of Basic and Top Events Failure Probabilities

Event	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
B1	0.04991	0.048	0.09052	0.1291	0.1684	0.2005	0.1939	0.2285	0.2571	0.2858
B2	0.02421	0.0241	0.04515	0.06311	0.06232	0.06106	0.0605	0.05869	0.05812	0.07461
B3	0.02472	0.02442	0.02384	0.02368	0.02348	0.02233	0.02222	0.02203	0.02154	0.02143
B4	0.050	0.04855	0.09348	0.08974	0.0879	0.1232	0.119	0.112	0.1493	0.1418
B5	0.009899	0.009767	0.009718	0.009641	0.009633	0.009594	0.009537	0.009525	0.008724	0.008201
B6	0.05	0.04779	0.04584	0.04431	0.04212	0.0396	0.03905	0.03782	0.03686	0.03524
B7	0.04952	0.04901	0.08804	0.123	0.1195	0.156	0.1493	0.143	0.1755	0.2034
B8	0.04903	0.04837	0.045	0.04334	0.04283	0.04031	0.03935	0.03724	0.03626	0.03537
B9	0.04919	0.04677	0.0466	0.04559	0.04265	0.04201	0.04138	0.04003	0.03924	0.03715
B10	0.05	0.04779	0.04584	0.04431	0.04212	0.0396	0.03905	0.03782	0.03686	0.03524
B11	0.07855	0.07598	0.07409	0.07089	0.06928	0.06472	0.06294	0.06165	0.05955	0.08822
B12	0.04918	0.04896	0.04631	0.04499	0.04242	0.04275	0.03941	0.03985	0.03837	0.03716
B13	0.04903	0.04837	0.045	0.04334	0.04283	0.04031	0.03935	0.03724	0.03626	0.03537
B14	0.05	0.04779	0.04584	0.04431	0.04212	0.0396	0.03905	0.03782	0.03686	0.03524
Top	0.081898	0.078241	0.127172	0.171488	0.208304	0.242325	0.233687	0.265751	0.29711	0.336343

Table 5: Posterior average failure probabilities of DPB basic and top events

Event	Prior (P)	Posterior average (POA)	Ratio (POA / P)
B1	0.050	0.165173	3.30346
B2	0.025	0.053187	2.12748
B3	0.025	0.022969	0.91876
B4	0.050	0.101497	2.02994
B5	0.010	0.009424	0.94239
B6	0.050	0.041863	0.83726
B7	0.050	0.125627	2.51254
B8	0.050	0.04171	0.8342
B9	0.050	0.043061	0.86122
B10	0.050	0.041863	0.83726
B11	0.080	0.070587	0.882338
B12	0.050	0.04294	0.8588
B13	0.050	0.04171	0.8342
B14	0.050	0.041863	0.83726
Top	0.0613	0.204232	3.331683

5.0 CONCLUSION

The study developed causal models of accident prevention barriers failures triggered by man-made and natural hazards that are regarded as high level contributed hazards in CPIs accidents. This article will be as introduction of future work to develop a more comprehensive CPI accident model through combined NE&SHs with the operational and technical as introduced in SHIPP model. Furthermore, the study has demonstrated the use of Bayesian network (using HBA) in precursor based approach to update the failure probabilities of FTs basic events which consequently led to update the failure probabilities of accident prevention barriers.

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